Overconfidence, Position Size, and the Link to Performance.

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ABSTRACT

The overconfidence literature employs activity metrics such as account turnover and trade frequency to link misattribution/self-attribution to excess trading. In this paper we argue relative position size is a more meaningful indicator of overconfidence. Using a sample of retail traders, we find that when traders take relatively larger positions they make more impaired trade entry/exit timing decisions. The opposite is seen when they trade more frequently. We also observe that more sophisticated and experienced traders trade relatively smaller positions and exhibit less overconfidence, consistent with these individuals suffering fewer behavioral biases, for which a likely learning effect is observed.

JEL Classifications: G41, G11, G32

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1 Introduction

A key feature of the investor overconfidence literature to-date is the link between this type of behavioral bias and increases in trading turnover[1] and one of its components, trade frequency.[2] There is however a second component to turnover - position size (or volume). If one accepts the established view that increased turnover indicates overconfidence, then we can infer a probable link between increased position size and overconfidence; especially if there is any cause to believe that increased trade frequency does not clearly demonstrate overconfident trading, which appears to be the case. Through the analysis of trading performance with respect to position size, and how it contrasts to trade frequency, this paper seeks to enhance our understanding of how overconfidence is expressed by the actions of market participants and how it impacts on their outcomes.

Position size has seen relatively little focus in the literature to-date, with Ben-David, et al. (2018) being the notable exception in their examination of self-attribution with respect to past performance; finding prior returns predict future trading activity. We extend this literature in a number of meaningful ways. Due to Ben-David, et al. (2018) lack of account cash balances data, it requires them to make a critical unstated assumption that all trades have a consistent relative trade transaction volume with respect to account assets. Specifically, the authors hypothesize that changes in trade size are the result of deposits to and withdrawals from their account. Barber and Odean (2000) make a similar unstated assumption with respect to their analysis of turnover. However, our findings indicate

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[1] Barber and Odean (2000); Barber and Odean (2001); Benos (1998); Glaser and Weber (2007); Graham, et al. (2009); Grinblatt and Keloharju (2009); Odean (1998); Pompian (2006); Statman, et al. (2006).

[2] Ben-David, et al. (2018); Feng and Seasholes (2005); Graham, et al. (2009); Grinblatt and Keloharju (2009); Linnainmaa (2011).

neither assumption is valid as relative transaction volume shows considerable variability and that variability has a clear link to trader performance. Further, we argue these inherent assumptions distance the analysis of overconfidence from transaction level risk-related decision making. While Ben-David, et al. (2018) may be correct in asserting that changes in account funding reflect changes in confidence levels, this we suggest is more a macro level confidence. In contrast, the availability of cash balances in our dataset allows us to examine position size – and by extension turnover – enabling us to focus more on the decision making at the individual trade level through the examination of the relative market exposures taken.

Also, investigating position size is important as the current literature on trade frequency is inconclusive as to whether it is, in fact, a strong indicator of overconfidence given increased trade frequency is not necessarily the product of overconfidence. Or, if it is, excessive trading may not actually result in diminished performance. For instance, Deaves, et al. (2009) and Biais, et al. (2005) find that overconfidence does not lead to higher trading frequency. Garvey and Murphy (2005) observe no link between the number of trades executed and trader performance, while Abbey and Doukas (2015) actually note increased trade frequency being linked to higher returns - the opposite of an overconfidence argument (see also Li, et al. (2016)). Graham, et al. (2009) find more experienced investors trade more often. If investors learn to overcome behavioral biases - a feature of the Gervais and Odean (2001) model supported by the Feng and Seasholes (2005) - this suggests experienced traders will trade less frequently, not the opposite.

The evidence therefore suggests other factors than merely overconfidence are at work when investigating trade frequency. For example, higher trade frequency may be the product of a learning process. Mahani and Bernhardt (2007) propose a learning model of speculation which features small-scale trading by inexperienced traders as they seek to discover their skill level. They argue that while inexperienced traders may trade more actively in frequency terms during the learning process, they may not actually trade at very high relative turnover levels. Linnainmaa (2011) supports this idea, at least in part, by finding that some traders use very small positions to learn about their ability. Thus, there theoretically exists a group of market participants who may be trading more frequently than rational expectations would suggest, but doing so on a relatively small scale. This is very similar to the trading pattern proposed by Grinblatt and Keloharju (2009) in terms of sensation-seeking individuals. It is therefore difficult to differentiate learning from behavioral bias based on trade frequency.

Position size, on the other hand, we argue, is a less noisy measure of overconfidence than trade frequency. It is also likely the last decision made by individuals who speculate on price action before they enter a new long or short position, after their point risk assessment. The decision-making on trade size is a function of the investor's available capital and access to leverage as constraints. The final determination, however, is based on the perceived riskiness of the trade, which is subject to the influence of overconfidence. As Kahneman and Riepe (1998) note, overconfident individuals underestimate the likelihood of negative outcomes outside their control, such as the movement in the price of a financial instrument. It is also in that excitement prior to initiating the trade that emotional influences can be most impactful (Kuhnen and Knutson, 2011), particularly for less experienced investors. This combination of factors can lead to individuals taking greater risks than would be prudent - in the form of excessively large trades. If an investor's risk perception is lower due to overconfidence, then they could rationally (to their mind) increase position size to match the risk they otherwise would take.[3] Moreover, if there is a potential learning aspect for new-career investors we

[3] For example, less experienced traders may not understand, or fail to consider, the probabilities of a given price move. This can lead them to set their stops too tight; believing they are taking less risk, allowing them to increase their position size. Resulting in their stops being hit more frequently than they expect.

would expect, as suggested by Linnainmaa (2011), traders to start with smaller rather than larger positions; opposite to the learning perspective of trade frequency.

To investigate the link between position size and overconfidence, and to determine whether it is a more meaningful metric compared to trade frequency, we utilize a dataset comprising more than 5,000 active traders who, during the period July 2008 to April 2013, executed a total of over 4 million trades worth nearly $195 billion in notional value. As the market focus for our traders is foreign exchange, where transaction costs are almost entirely determined by spread costs, comparable changes in either the number of trades or their size produce the same impact on net returns (spread costs rise in line with total traded volume). We are therefore able to investigate specifically whether increased trading frequency or position size is indicative of overconfident trading, and if so whether overconfident traders make worse entry/exit timing (trade timing) decisions (Burks, et al., 2013). If so, we would expect to see a reduction in their per-trade returns when stripping out trade size considerations and looking only at the price movement captured by each trade.

We find that traders who increase relative position size (*RPS*) - trade size relative to total account value - do not suffer lower net returns simply because of larger positions. They also exhibit increased trade timing impairment (i.e. they make worse trades) consistent with an overconfidence bias. In other words, not only do these traders make larger losses on average because they trade bigger positions in the face of negative expected returns, they reduce their returns further by doing a worse job of picking entry and exit points. Conversely, we find that those traders who increase their trade frequency make better trade timing decisions. Their entry and exit decisions are improved such that when they trade more often they offset the cost of the additional trades – at least partly. In fact, we also observe that trade timing performance follows the same pattern for overall turnover as for trade frequency. Higher turnover is associated with improved trade timing. These findings support our hypothesis that position size is the more meaningful indicator of overconfident trading and provide a new layer to the literature with respect to the link between overconfidence and excess trading. These findings also have potential regulatory considerations, such as those discussed by Heimer and Simsek (2018).

To further corroborate position size as an indicator of overconfidence we also investigate whether inexperienced investors suffer more from behavioral biases, as suggested by the literature.[4] Consistent with expectations, we find increased relative trade size among inexperienced traders is significantly associated with poor trade timing, unlike the case of experienced traders. This contrasts with the findings of Oberlechner and Osler (2012) with respect to currency dealers, but supports the observations of Nicolosi, et al. (2009) and Seru, et al. (2010), who both link experience to improved performance. Moreover, we find that a reduction in relative position size is a function of learning rather than simply individual proclivity. Experienced traders did not become experienced simply because they traded smaller positions (presumably resulting in smaller losses). They reduced their relative position size over time. We also observe that traders with larger accounts tend to take relatively smaller trades, and that they do not exhibit the same negative link between trade timing performance and relative position size. This is consistent with the findings of Feng and Seasholes (2005) that sophisticated investors – at least judged on the basis of investment capital, which is often the case from a regulatory perspective – are able to reduce the influence of behavioral bias.

Following these results, we also investigate the type of overconfidence theorized to drive increases in trading activity - namely misattribution/self-attribution.[5] In line with Ben-David, et al.

[4] Feng and Seasholes (2005), Gervais and Odean (2001), Nolte and Voev (2011).
[5] Daniel, et al (1998), Gervais and Odean (2001), Glaser and Weber (2009).

(2018), we find that prior period returns influence both trade frequency and relative position size. However, in addition we also observe it in the traders' instrument selection process, which factors into the expected trade volatility part of increased risk taking.

In addition to our contribution with respect to overconfidence-linked overtrading and learning, as noted above, this paper also extends the literature on the subject of retail speculators – and even professional speculators with respect to their ability to overcome behavioral biases. There is, perhaps, the inclination to believe retail forex traders are somehow different than those in other markets, particularly equities. Based on the literature, however, equity and forex speculators appear to have much in common. For example, Barber, et al. (2014) estimate that less than 1% of day traders in the equity market are reliably profitable. The daily returns they describe are comparable to the ones seen in our sample. Given that behavioral biases are not isolated to particular markets, this is to be expected. While forex traders may have more variation in relative position size than is the case in equities, we argue the two are probably quite comparable in terms of trade frequency. Traders in both markets exhibit clear indications of disposition effect influences. Furthermore, our analysis focuses on changes rather than absolute levels. As such, our findings should be representative of patterns exhibited across markets.

The remainder of this paper is structured as follows. Section 2 describes the dataset employed and measures constructed for our analysis. Section 3 reports the results of the analysis, along with sensitivity tests. Section 4 concludes.

2 Data & Measurements

2.1 Data

For our analysis we use a dataset of retail spot foreign exchange trader accounts. Although this market is relatively new with respect to prior research, it provides some generalizable indications as noted by

Ben-David, et al. (2018). Our dataset is very similar in terms of participants and activity level to the one employed by Ben-David, et al. (2018), but with a broader geographic scope, and is comparable to the Hayley and Marsh (2016) sample. It is identical in source to the dataset used in Heimer (2016), as well as Simon and Heimer (2012), Simon (2013), and Heimer and Simsek (2018), although it covers a longer time period. In terms of participants, the dataset is similar to one used by Nolte and Voev (2011), but their sample only includes a single month‘s trading with traders from just a single broker - albeit with more traders involved. It is also similar to that used by Abbey and Doukas (2015).

As in the case of Ben-David, et al. (2018), our traders exhibit characteristics similar to traders from other observed markets, indicating that our findings should apply generally across markets. Our traders clearly demonstrate indications of disposition effects in that they win more frequently than they lose, and the losing trades are much larger and are held significantly longer than the winners. Further, while there are indications that the traders in our sample are above average (see Section 2.6 for details), they on average earned negative abnormal returns. This is in contrast to Abbey and Doukas (2015), who find that their individual currency traders earned positive abnormal returns. However, this is not unexpected, as their sample is limited to traders who earn profits by allowing others to duplicate their trading activity - known as “social” or “copy” trading.[6] In other words, they focus on a sub-sample of presumably profitable traders and consequently, their results are not generalizable to all retail traders.

Our sample was aggregated by a social network of retail forex traders, which formed in early 2009. Participation in the social network was free but required members to link the online platform to their live account(s) at one of approximately 50 connected brokers. Connecting granted the

[6] See Forman (2016) for a description of this process.

platform the ability to collect data in real time from those linked accounts - to include transactions executed, orders entered, and positions held - by capturing all activity moving forward from registration. In some cases, the platform also collected historical transaction information available in the account.[7] Members had no ability to filter out any of the actions taken in their linked account(s), removing any concern about reporting accuracy or selectivity.[8] In our analysis we include trading pre and post membership where available. In unreported results (see section 3.6.) we control for the possibility membership may change trader behavior by including an indicator variable. We find our results are not sensitive to this specification.

The sample period for our dataset is from July 2008 to April 2013 for a total 58 full months. There are 5,502 active members[9], accounting for 35,060 total trader-month observations. In addition to the transaction log, we also obtained a daily summary table, which provides us with the daily returns, account balance, and other related information for each trader. Unlike the transaction log, the data from the daily summary table was largely calculated by the social network platform at the end of each day. On inspection, it contained a few errors.[10] We exclude those observations with erroneous values from our analysis, reducing our sample to 5,349 active members with a total 33,633 of observations. We discuss the composition of the sample in more detail in Section 2.6 below.

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[7] There was historical data collection only for some of the membership either due to technical limitations or the simple lack of any data to collect (new trader and/or new account).

[8] It should be noted that the social network in question was closed in 2014 after being acquired by one of the large global retail aggregators (brokers).

[9] There are 7810 members in the dataset with at least one transaction recorded. However, after excluding those for whom the account currency is unknown (making it impossible to derive turnover and relative positions sizes) and eliminating highly suspect records, the usable number drops to 5,502.

[10] Specifically, several negative account balances were discovered which appeared to be a function of a faulty pre-membership historical data retrieval process. Following discussions with the administrators of the network, they corrected for these going forward, but nothing was done with the existing dataset. We also excluded observations where position size was excessively large relative to the account's capital (even by retail forex standards) as likely including erroneous values in terms of account balance.

2.2 Returns

Using the daily returns data noted above, we calculate two monthly return values. The first is a basic monthly compounded return, which is derived by sequentially multiplying the net return on investment (*ROI*) values for each active trading day during the period in question, where "active" in this context means having at least one open position during some point in the day, and investment is account balance (cash + open trade equity).

$$Return_i = ROI_{1,i} \times ROI_{2,I} \times \ldots \times ROI_{n,i} \tag{2.1}$$

Where i is a given month and n is the number of active trading days in month i. Thus, $ROI_{1,i}$ is the *ROI* for the first active day in month i, $ROI_{2,i}$ is the *ROI* for the second active day in month i, and so on. In the case of those members with multiple accounts linked to the social network (approximately 25%), we aggregated their activity and performance. The monthly return value for this group of members is derived using the USD-equivalent account balance of all active accounts in the period to weight each account's return.

The second return measure we derive is an average trade return. We use this additional metric in our analysis in Section 3 to specifically examine trader performance when stripping out the trade frequency and position size considerations which factor heavily into monthly returns; our focus of interest. This is calculated based on the exchange rate change for each round-turn position. In doing so we remove from consideration positions sizes, which factor into the overall monthly return.

$$LongTrade\_Return = \left[\frac{\text{Exit Price}}{\text{Entry Price}}\right] - 1 \tag{2.2}$$

$$ShortTrade\_Return = 1 - \left[\frac{\text{Exit Price}}{\text{Entry Price}}\right] \tag{2.3}$$

Given our focus is forex trading, the prices above are the exchange rates indicated at the time of entry and exit. Consistent with Ben-David, et al. (2018) the aggregated monthly return values are calculated as follows:[11]

$$CummulativeTrade\_Return_i = \sum_{t=1}^{n_i} Trade\_Return_{t,i} \tag{2.4}$$

Where i is a given month, t is a trade taking place in month i, n_i is the number of trades executed in month i and *Trade_Return* is either *LongTrade_Return* or *ShortTrader_Return* per the directionality of transaction t,i. Note that for trades which carry over from one month to the next we count them in the month they were initiated, as the entry decision relates to our focus of interest - traders' overconfidence.

From the cumulative return we derive and average trade return as an indication of trader skill (trade timing performance).

$$AverageTradeReturn_i = \frac{CummulativeTrade\_Return_i}{N_i} \tag{2.5}$$

Where i is a given month and N is the number of trades executed in month i.

This average trade return has the benefit in allowing us to focus on the trader's skill with respect to their trade timing (entry and exist decision) as a major factor in determining monthly returns. Both return metrics generally carry the same sign, though if there is variations in trade size the two measures may deviate in that regard. For example, consider ten trades made in a month, nine of which result in 2% gains and one in a 10% loss. Thus, the average trade return for this month, as defined

[11] Because of the small returns of these trades (the 25th to 75th percentile range of individual trade returns is from -1.20% to +1.16%), the lack of compounding is unlikely to create a meaningful return distortion relative to any potential compounding effect there is in the actual returns. Likewise, since the clear majority of trades are short holding periods (more than 50% held less than 12 hours), not including the influence of interest carry is also unlikely to be problematic.

above, is 0.8%. If all ten trades are for positions using 50% of available capital then the monthly return is 4% [(9 x 2% x 0.5) + (1 x -10% x 0.5)], not factoring in any compounding impact. However, if all the trader's winning trades came while using 50% capital, but their single losing trade came while using 100% capital, the monthly return falls to -1% [9 x 2% x 0.5) + (1 x -10% x 1)] while the average trade return remains the same. This lower monthly return is therefore not the result of a change in the trader's entry/exit timing ability, but because of the decision to double the size of that transaction – a decision linked to overconfidence, whether one considers it in terms of the impact on monthly turnover or from the perspective of average RPS. On the other hand, the average trade return measures a trader's skill, irrespective of the position size, which could also be impacted by overconfidence per Burks, et al. (2013) and Kahneman and Riepe (1998). Thus, if overconfidence leads to *both* increased trading activity *and* diminished trade timing performance, it could result in a compounded negative effect on monthly returns.

2.3 Turnover

Turnover is derived for each trader-month as the total USD-equivalent volume traded that month divided by the average USD-equivalent account balance (cash + open trade equity).

$$Turnover_i = \frac{\sum_{t=1}^{n_i} Volume_{t,i}}{Average Account\ Balance_i} \qquad (2.6)$$

Where i is a given month, t is a transaction taking place in month i, and n_i is the number of transactions executed in month i. We use average monthly account balance rather than the observation from a fixed point as it allows for the accounting of any deposits or withdrawals, interest carry, and the impact of trade performance on account value. Only days on which trading activity took place (including holding open positions) are included in the average, which allows turnover to reflect the account balances during periods of decision-making.

It should be noted that our calculation of turnover varies from Barber and Odean (2000). They used the value of all open positions at the start of the month as the denominator in the turnover equation, not total investor capital in the account as we do (since cash positions were not included in their dataset). In doing so Barber and Odean (2000) effectively assume all investors have the same proportion of their capital in the market. For example, Investors A and B in their analysis would have the same turnover rate if each started the month with $50,000 invested and did $50,000 in transactions. Both would be 1.0, even if Investor A had $100,000 in total capital and Investor B only had $20,000. In our calculation, Investor A's turnover would be 0.5, while for Investor B it would be 2.5.

2.4 Relative Position Size (***RPS***)

As suggested by Ben-David, et al. (2018), changing position size is a way to evaluate prospective changes in risk-taking. However, due to the lack of account balance information in their dataset (as they do not have cash position data), the authors opt to use changes in average trade size as their metric. They rightly note that the addition of new capital to a trader's account is a likely indication of the willingness to take additional risk, which means the opposite could also be the case. This may be the case, though it could also be argued that this represents a more macro level of personal confidence rather than the more micro trade-to-trade or period-to-period level confidence. Even if account funding changes did operate on a more micro level, given the fairly small size of most retail forex trader accounts (see Section 2.6), and the potential use of high leverage, meaningful variance in average trade size could be a simple function of changes in account balance related to gains and losses in the market. That means it may have nothing to do with variation in risk-taking. Further, changes in position size may not reflect changes in account balance at all, which most likely means they *do* reflect variation in risk-taking. We clarify this issue by using available account balance information, inclusive of cash balances, to derive Relative Position Size (*RPS*). We calculate two alternative measures of *RPS*. The first measure is:

$$RPS_i = \frac{Turnover_i}{N_i} \tag{2.7}$$

Where *Turnover* is as derived from Equation (2.6) and N is the number of trades entered in month i. We use average account balance for the trader's account(s) for the month during which the trade took place to maintain consistency with the measure of *Turnover* since position size is one of the constituents of *Turnover*, along with trade frequency. The second measure of *RPS* is the aggregation of the individual trades during the month as follows:

$$RPS_i = \frac{\sum_{t=1}^{n_i} {Volume_{t,i}}/{Account\_Balance_{t,i}}}{N_i} \tag{2.8}$$

Where *Volume* is the size of trade t in month i and *Account_Balance* is the account value at the time of trade t. Thus, we have a mean of all the individual trade RPS values rather than RPS being based on the aggregate values and mean account value. If we remove the division by N_i we have a value for *Turnover* derived on this same basis. This second measure avoids the criticism that the denominator in Equation (2.6) is a value that it not established until the end of the month and not at the time the investor is overconfident. Our findings are not sensitive to the alternate specifications, so for the sake of brevity our results in Section 3 use *Turnover* and *RPS* values derived per Equations (2.6) and (2.7) respectively, consistent with the existing literature.

A limitation of *RPS* as an indication of a change in risk appetite – similar to the use of the change in trade size variability metric employed by Ben-David, et al. (2018) to judge trader perception of skill – is that a trader can take the exact same risk while changing position size. For example, consider the situation where a trader wants to risk 1% of their capital on a trade. Where they decide to put their stop dictates the trade size which equates to a position with that level of risk. If the stop placement is a 1% market move, then position size will be 1X. If, however, the stop point is 0.5%, then position size is 2X. Unfortunately, we cannot fully capture this sort of thought process, however we do at least capture any part of it which reflects the trading of different exchange rates, and the change in expected market volatility that is involved as part of the risk-taking process.

2.5 Bid/Ask Spread

A second method of evaluating the riskiness of a traded position is the liquidity and volatility of the market traded. This is captured in the bid/ask (or bid/offer) spread. The link between the spread and both liquidity and volatility is well established in the literature (Bessembinder, 1994; Bollerslev and Melvin, 1994; Wang and Yau, 2000).

We were unable to obtain the actual spread of a given exchange rate at the time of each trade. As a result, we use a snapshot of the spreads from a major retail forex broker during an active time of day as an estimate. We acknowledge that this may underestimate the spreads generally given the higher liquidity of that period. Using these estimates, we derive a bid/ask spread return for each trade. This is calculated by dividing the estimated bid/ask spread for the currency pair in question by the exchange rate at the time the trade was entered. Since the spread always works against the price taker, which is the majority of the market, we express these spread returns as negative values. For example, if a trader went long EUR/USD at 1.30000 with a spread estimate at 1.5 pips (0.00015) then the spread return is estimated to be -0.0115% (-0.00015/1.3). We then average the estimated trade bid/ask return values across all trades undertaken by an individual trader in a given month on an equal weight basis. Changes in this value from month to month thereby provide an indication of a change in exchange rates traded, and by extension a shift in the liquidity/volatility of the markets traded.

2.6 Descriptive Statistics

Table 1, Panel A provides descriptive statistics on the trading activity and performance of our sample. The mean (median) monthly account balance of traders (*Balance*) is $14,643 ($1,511) with an average number of trades (*NTrades*) of 74 per month (median 22), and a mean (median) duration of trades each month of 3.63 (0.45) days.[12] The mean (median) monthly account turnover (*Turnover*) is 498 (107) times the trader account balance, while the mean (median) relative position size (*RPS*) is 12.96 (4.90) times the account balance per trade. The mean (median) number of months of trading data we have for each trader is 6.29 (3), with a mean (median) of 8.91 (4) calendar months. Overall, our sample comprises mainly of small, high frequency traders who have a relatively short trading lifespan. The authors have seen unofficial indications that the average account lifespan in retail forex in general is about 180 days, in line with our sample. At present, however, this kind of data is not publicly available from the brokers.[13] Unsurprisingly, given the negative sum nature of the market, the mean (median) monthly return for the traders in our sample is -5.94% (-1.83%) with an average (median) trade return, of -0.05% (0.0094%). Compared to a set of US-based brokers reported by Forex Magnates[14] our traders' performance is above average (see Panel B). On average, the US-broker figures indicate that

[12] It should be noted that while retail forex positions are rolled forward at the end of each trading day, this does not produce a position closure and the opening of a new position each day in terms of the record-keeping. Thus, a trade which lasts five days does not count as five separate trades.

[13] An industry source indicated that this is not made public as it "is embarrassing to the brokers", and while such information is reported in the case of acquisitions, it is subject to non-disclosure agreements.

[14] There is currently no public data on trader returns for the whole forex market. We could only obtain data for US-brokers who are required by the Commodity Futures Trading Commission (CFTC) to report quarterly indications of the fraction of their active accounts which finished that period with a profit.

30.8% of accounts are profitable each quarter. The traders in our sample are profitable, on average, 38.9% of the time. This continues to hold true when we just focus on our sub-sample of US traders.

Panel C provides data on the traders' demographics. Traders in our sample had the opportunity to disclose their experience level by indicating which category best described their years of prior trading - 0-1 year, 1-3 years, 3-5 years, or 5+ years; their country of origin - Unites States, Europe, or Asia/Pacific; and trading style – technical, fundamental, momentum and news. Not all traders disclosed this information. Of the 78% of members who did, 21.6% indicated 0-1 year of experience, 32.4% 1-3 years category; 9% listing 3-5 years, and 17% in the 5+ years category. A total of 32.7% of the traders are from Europe, 26.4% are from the United States, and 16.87% from Asia/Pacific region.

Unsurprisingly, the most frequently identified trading style was technical analysis, consistent with Ivanova, et al. (2016). It could be suggested that since high frequency traders are very biased towards using technical analysis for their trade decision-making, they may be "forced" to let profits run and cut losses via this type of approach. As such, a trend-following strategy could be profitable despite experiencing more losers than winners. However, this assumes that all technical analysis methods are trend-following in orientation, which is not correct. Second, the mean holding period for winning trades in our dataset is 1.16 days, as opposed to 2.08 days for losing trades. That provides some indication of probable disposition effect impacts, and evidence that traders are not letting winners run. Finally, we observe more winning trades than losing ones.

Table 2 provides details of the currencies and currency pairs most frequently traded by our sample. For the purpose of comparison we also include in Table 2 the volume proportions reported from the spot market data in BIS (2014). Overall, we find 88.8% of our traders traded in the USD which is comparable with the BIS data reporting 82.6%. However, the proportion of EUR was 72.1%, which is significantly different from the BIS at 36.9%. In terms of currency pairs, there is a clear preference among our sample of traders to trade EUR/USD, which is nearly twice that of the BIS figures. This may reflect a rational choice among our high frequency traders to operate in the most liquid, low cost (smallest bid/ask spread) currency pair. The idea traders potentially make a rational strategic level decision is not contrary to the idea they are irrational when it comes to individual trade choices as they operate in different time scopes and with different potential emotional implications.[15]

We also acknowledge that there may be a selection bias with respect to the overconfidence level of individuals who joined the social network. For example, network members may be generally more or less overconfident than the average retail forex trader. Lacking general market figures, we just cannot know. However, because we focus is on individual changes rather than absolute levels, we do not believe this is a significant concern to our subsequent inferences.

3 Results

3.1 Univariate Analysis

We replicate Barber and Odean (2000) to seek confirmation that turnover is associated with impaired trader returns in our retail forex setting. To do so, we employ the same quintile-based methodology to compare investor performance across relative levels of trading activity.

In the foreign exchange market there is no market return, nor factors equivalent to the Fama-French SMB or HML metrics. Although Pojarliev and Levich (2008) develop factors based on carry trade, trend, value, and volatility based strategies for their analysis of professional currency managers,

[15] We also observe that the traders who did not indicate an experience level in their profiles exhibit a very different volume pattern to the rest of our sample. Further analysis finds excluding these traders does not influence our findings, as noted in our robustness tests in Section 3.6. below.

this approach is challenged by Melvin and Strand (2011) on the basis of the lack of a market portfolio and buy-and-hold investing in currencies. The very short time frames of the traders in our dataset is a dramatic example of the latter. This limits our ability to produce a comparable benchmark return adjustment. Barber and Odean (2000) constructed their own-performance benchmark based on the returns which would have been achieved had no portfolio change been made by a given investor (in other words, as if the investor just held the positions they had at the start of the month). Following a similar line of analysis is, however, not possible due to the high frequency nature of forex trading. Given the high proportion of day trading, we must work from a basis that most traders have no position to start the month. As such, if the trader in question made no trades their return would be zero, making our own-benchmark return zero.

We construct the quintiles on a monthly basis[16], allowing traders to change quintiles as they are more or less active from month to month. Thus, we capture time-varying levels of potential trader overconfidence. Each trader-month is assigned a quintile based on its relative ranking for that month. All observations are then aggregated by their quintiles to determine univariate mean values.[17]

Table 3, Panel A reports the descriptive statistics for the quintiles in addition to the statistical variation between the least active (Q1) and the most active quintiles (Q5). Consistent with prior

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[16] We also used fixed quintile membership rather than allowing it to fluctuate on a monthly basis. This was accomplished by aggregating each member's data across all their active months and placing them in a quintile based on their ranking relative to all members. Doing so, we hold membership classification fixed across all observation periods, allowing for analysis on the basis of the traders' general behaviour rather than activity which may be reflective of monthly vagaries. However, the pattern of returns derived from these alternative quintiles remained unchanged.

[17] Unfortunately due to lack of data availability we were unable to pursue additional analysis with respect to (i) the actual level of risk traders take at position entry based on where they place their stop loss (assuming they use one) and therefore measuring overconfidence at the time of trade entry; and (ii) whether traders alter positions sizes once trades are entered – for example, "doubling down" if the initial market move was against them.

literature, we find higher levels of turnover equate to worse trading performance. The difference in returns between the quintiles is significant. The fifth quintile has returns 1671bp lower than those of the first quintile (-17.76% vs -1.04%). However, given the skewness in the data, this is partially reflective of a wide dispersion of values in the highest category. As our returns include spread costs, they align with the net returns outlined in Barber and Odean (2000).

We also observe that average account balance declines noticeably across the turnover quintiles - from $18,331 for Quintile 1 down to $5,300 in Quintile 5 - indicating the smallest accounts trade more actively. Trade frequency (*NTrades*) and *RPS* both rise over the quintiles. These observations are not surprising, but call into question the idea that higher turnover is simply a reflection of a shorter time frame effect if we expect more frequent, shorter term trading to mean relatively smaller positions.

Panels B and C in Table 3 report the quintile analysis for the turnover components: trade frequency (*NTrades*) and relative position size (*RPS*) respectively. Overall for both *NTrades* and *RPS* as we move from Quintile 1 to Quintile 5 returns decline significantly, similar to the *Turnover* quintiles.

However, we observe in the case of *NTrades* that *Balance* rises across the quintiles. The mean of the account balance with respect to *NTrades* (Panel B) for those in Quintile 1 is $6,866, rising to $32,363 for Quintile 5. If one argues, consistent with prior findings (Agnew, 2006; Li, et al., 2016), that those individuals with larger accounts are likely to be more sophisticated traders, then we have some evidence to suggest informed traders are more frequent operators in the market. This in turn may suggest that trade frequency is not a strong indicator of overconfidence. Although mean monthly turnover does rise across the trade-based quintiles (from 142 to 1454), it is clearly driven by increased trade frequency as average *RPS* falls from 18.74 in Quintile 1 to 6.72 in Quintile 5.

In Panel C the quintile returns for *RPS* are very similar to those from *Turnover*, moving from -0.42% in Quintile 1 to -17.04% in Quintile 5. The change from least to most active is only 5bp smaller for *RPS* than for *Turnover*. By comparison, when looking at the *NTrades* quintiles in Panel B we see them start at -4.00% in Quintile 1, then progress steadily up to -8.89% in Quintile 5. The implication seems to be that trading relatively larger positions has more of a negative impact on monthly returns than trading more frequently.

This analysis appears to confirm that excessive trading – likely motivated by overconfidence – tends to lead to diminished returns, and that trading bigger positions seems to more negatively influence returns than trading more frequently. However, there is an inherent bias in our dataset. The monthly return findings are consistent with a negative sum game (reflected in the average trade returns reported in Table 1). Thus, if you trade more, then on average you increase your expected losses. This is different from the equity market where you can still have a positive expected return even if you increase your turnover, as observed by Barber and Odean (2000). That being the case, observing more trading activity leading to higher losses in our context does not provide any indication as to whether these higher losses are simply a function of a mathematical expectation or whether there is more granularity involved. Specifically, are traders making better or worse trade timing decisions? If increased activity indicates overconfident trading, and overconfident traders make worse trade timing decisions (Burks, et al., 2013; Kahneman and Riepe, 1998), we would expect to see a reduction in not just overall monthly returns, but also average-trade returns across the quintiles, since changes in monthly returns are not just a function of the basic mathematics of increased trading activity. It is therefore useful to examine the quintiles in that context.

Analysis of the quintiles with respect to average trade returns is reported in Panel D of Table 3. We find in the case of both *Turnover* and *NTrades* trade returns increase as we move from the least active to the most active quintiles, potentially contradicting the findings in Panels A and B. However, the average trade return never turns positive. For example, the Quintile 5 average trade return loss for

NTrades from Panel D is less than a tenth that of Quintile 1 (-0.00013 vs -0.00138) while the mean *NTrades* for Quintile 1 in Panel B is 2, while for Quintile 5 it is 281. Traders on average are making more than 100 times as many trades in Quintile 5 than in Quintile 1, more than offsetting the dramatic improvement in average trade returns. The result is larger monthly return losses for those in Quintile 5 over those in Quintile 1 even though they seem to exhibit better trade timing ability. In the case of *RPS*, average trade returns decline, but not significantly. Thus, while it may be true that increased trading activity reflects overconfidence, as it still leads to decreased monthly returns, there is a clear difference in what that means when discussing trade frequency verses *RPS*.

We therefore undertook a two-way sorts on the two turnover components - specifically sorting on trades quintiles, then *RPS*, and also the reverse. Panel E of Table 3 reports the results for monthly returns, while Panel F reports the results for average trade returns. Overall, the results in Panel E confirm the prior analysis from Panels B and C above; changes in *RPS* quintiles tend to have a greater influence on monthly returns than changes in *NTrades* quintiles. Similarly, the results in Panel F support our observations with respect to average trade returns. Most notably, when the primary sort is on *RPS* we consistently find the pattern of trade returns showing the lowest in *NTrades* Quintile 1 and the highest (markedly) in *NTrades* Quintile 5. But when the primary sort is on *NTrades* there appears to be no strong pattern with respect to the *RPS* quintiles. To seek to better understand of the diverging influence of trade frequency and *RPS* on returns – both monthly and trade – we undertake a multivariate analysis.

3.2 Multivariate Analysis

To gain a deeper understanding of the relationship between trade frequency, *RPS*, and returns we construct the following two multivariate models controlling for trader characteristics:

$$Monthly\_Return_{j,m} = \alpha + \beta_1 NTrades_{j,m} + \beta_2 RPS_{j,m} + \beta_3 Balance_{j,m} + \beta_4 Month\_Count_{j,m} + \beta_5 Duration_{j,m} + \beta_6 Spread_{j,m} + \beta_7 Month\ F.E. + \beta_8 Trader\ F.E. + \varepsilon_{j,m} \quad (3.1)$$

$$Average\_Trade\_Return_{j,m} = \alpha + \beta_1 NTrades_{j,m} + \beta_2 RPS_{j,m} + \beta_3 Balance_{j,m} + \beta_4 Month\_Count_{j,m} + \beta_5 Duration_{j,m} + \beta_6 Spread_{j,m} + \beta_7 Month\ F.E. + \beta_8 Trader\ F.E. + \varepsilon_{j,m} \quad (3.2)$$

Where j is the individual trader and m is the calendar month. *NTrades* represents the number of trades initiated by trader j in month m and *RPS* represents the average *RPS* for the positions initiated by trader j in month m. If either component proxies for overconfidence we would expect β_1 and/or β_2, to be negative.

Both models control for investor characteristics. Following prior findings that sophisticated investors are less prone to behavioral biases like overconfidence (Feng and Seasholes, 2005; Gervais and Odean, 2001; Nicolosi, et al., 2009; Seru, et al., 2010) we control for traders' sophistication level using investor capital (*Balance*) as a proxy. Where *Balance* is the average account balance of trader j in month m as described previously in Section 2.3. Regulators and others often use investor capital as a way to differentiate individuals, as it is assumed those with more wealth are likely to be more financially savvy than those with less (Agnew, 2006; Ekholm and Pasternack, 2008; Li, et al., 2016). We therefore expect β_3 to be positive.

To control for the incremental experience gained by traders since joining the network, or reduced experience for months prior, we also include a month count variable (*Month_Count*). *Month_Count* is the number of months the investor has been a member of the social network, starting at 0 the month the investor joined, with negative values for entries prior to membership. For example, if a trader signed-up in January 2010, and traded in April 2010 the *Month_Count* value would be 3. We find that pre-memberships entries represent a minority (13%) of the total observations. We expect *Month_Count* to have a positive relationship to returns on the basis that skill increases with experience.[18]

To control for any variation in the individual's trading time frame, which may be indicative of a shift in strategy (or variation in disposition effect influence), we include *Duration,* the mean holding period (in days) of trades done by trader *j* in month *m*. We also include a proxy for the risk attitude of an individual trader, at least as expressed by their liquidity and volatility preference - *Spread* (the mean estimated bid/ask spread return of trades done by trader *j* in month *m*). As noted in Section 2.5, this variable captures the composition of the currency pairs traded. The narrower the average spread (the less negative the value of *Spread*), the more liquid the markets traded.

We include both month fixed effects to account for any general market conditions and trader fixed effects to capture the trader's individual time-invariant characteristics (such as reported experience level and trading style). Robust standard errors are clustered at the individual trader level. Given the positive skewness of *Turnover, NTrades, RPS, Balance* and *Duration* variables, a log transformation to those values is applied. All continuous variables, aside from *Spread* and *Month_Count*, are winsorized at the top and bottom 1%. *Spread* and *Month_Count* are not winsorized due to their values being well constrained.[19]

Table 4 reports the correlations among the monthly trade returns, average trade returns and trade characteristics. Consistent with the univariate analysis, both *NTrades* and *RPS* are negatively correlated to *Monthly_Returns*, at -0.07 and -0.23 respectively. Also consistent with the prior findings,

[18] An alternative specification for *Month_Count* was also investigated e.g. the count starts as soon as the trader starts trading (e.g. enters the data), not necessarily when they joined the network. Our results are not sensitive to this alternative specification.
[19] Further, in the case of *Spread*, the highest spread return values (least negative) are for EUR/USD, which is the most frequently traded currency pair by far.

NTrades is positively correlated (0.08) to *Average_Trade_Return*. The correlations, however, seem to show a somewhat stronger negative correlation (-0.05) between *RPS* and *Average_Trade_Return* than is suggested by the quintile analysis above. The contrary correlations for *NTrades* and *RPS* with respect to *Average_Trade_Returns* in part explains the large difference in the negative correlations between the two activity metrics with respect to *Monthly_Returns*. If we consider monthly return to be approximately the product of *NTrades* x *RPS* x *Average_Trade_Return*, adjusted for compounding, we would expect *NTrades* and *RPS* to have similar correlations, which clearly is not the case.

NTrades is positively correlated with *Balance*, suggesting larger traders trade more actively, and negatively correlated to *Duration,* indicating that they hold their position for a shorter time. *RPS* is negatively correlated with *Balance* indicating that more sophisticated traders trade relatively smaller positions. *RPS* is also negatively correlated with *Duration* which is consistent with nominal risk-taking - the expected volatility of an exchange rates is higher the longer you are in a position, so for a given level of desired account risk you would put on a smaller trade (lower *RPS*). *RPS* is positively correlated with *Spread* indicating traders are trading relatively larger positions in relatively less volatile currency pairs (recalling that higher *Spread* means less negative spread return values).

Of note, *Month_Count* is negatively correlated with both *NTrades* and *RPS*. This is consistent with traders learning to be less overconfident, to the extent that these two activity metrics capture that bias. The subject of learning is explored further in Section 3.3.

Table 5 reports the analysis for the two measures of returns; Columns (1) – (3) when the dependent variable is monthly returns and Columns (4) - (6) when the dependent variable is average trade returns. Specifically, Column (3) reports the estimates for Equation (3.1), with Columns (1) and

(2) reporting *NTrades* and *RPS* singularly respectively for a stepped progression.[20] The coefficients in the full model (Column (3)) for both *NTrades* and *RPS* are significantly negative at -244.4 and -426.7 respectively. Given the coefficients are expressed in terms of basis points, this indicates a significant impact on monthly returns from changes in the two activity metrics. The magnitude of the coefficient on *RPS* indiciates a significantly greater negative impact (75% larger) on *Monthly_Return* than *NTrades*, given equivalent changes.[21] As noted above, we would not expect to observe such a large difference on monthly returns from these two activity metrics, which suggests a compounded overconfidence effect may be present. For this reason, moving forward we focus on analysis with respect to trade rather than monthly returns.

Column (6) of Table 5 reports the estimates for Equation (3.2), with Columns (4) and (5) reporting *NTrades* and *RPS* singularly respectively for a stepped progression. Again, all the coefficients are expressed in terms of basis points. In Columns (4) and (6), the coefficient on *NTrades* is positive and highly significant, indicating a 1-point increase in the log of the average monthly number of trades results in a 2.45 basis point increase in the monthly average trade returns; or alternatively an increase of one standard deviation in monthly trade frequency increases average trade returns by approximately 2.64%. The opposite is true for *RPS*. In Columns (5) and (6) the coefficient on *RPS* is negative and highly significant. The coefficient on *RPS* in Column (5) indicates a 1-point increase in the log of the average monthly relative position size results in a 1.205 decrease in the monthly average trade returns;

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[20] Due to collinearity, one of the network member traders is dropped in the regression derivation, reducing our total trader-month observation count by four.

[21] In unreported results, we also ran the *Monthly_Return* regression including *Average_Trade_Return* as an additional independent variable. As expected, the coefficient on *Average_Trade_Return* is positive and highly significant. At the same time, its inclusion results in the coefficient on *NTrades* becoming slightly more negative and for *RPS* becoming slightly less negative; with the coefficient on *RPS* indicating 40% more influence on *Monthly_Return*. We retain the presentation of the results without *Average_Trade_Return* to maintain easy comparability across the tests and because the secondary finding does not alter the broader observation that *RPS* has a markedly larger impact than *NTrades*.

or alternatively an increase of one standard deviation in monthly average *RPS* reduces average trade returns by approximately 4.66%. While the coefficients for *NTrades* across the two specifications are similar, this is not the case for *RPS*, with a -1.341bp value for the full-model (Column (6)). This may not appear to be economically significant when considering average trade returns of -0.0501%, but when factoring in a mean (median) *RPS* of 12.96 (4.90) and monthly trade count of 74 (22) potentially we have a very large impact on monthly returns. Thus, this provides further evidence that there is a clear divergence between *RPS* and trade frequency with respect to their relationships to trade timing performance, in line with the univariate analysis in Section 3.1. As such there is strong evidence to support our hypothesis that *RPS* is a better indication of potentially overconfident trading than is trade frequency. These findings also suggest that trade frequency may not be a particularly good indicator of overconfidence, which is consistent with the conflicting evidence found in the prior literature.

Among the control variables, when monthly returns is the dependent variable the coefficient estimates for *Balance*. is positive and significant, suggesting sophistication, as measured by account capital, is beneficial to overall trader performance, consistent with the literature (Agnew, 2006; Ekholm and Pasternack, 2008; Li, et al., 2016). When the dependent is trade returns the coefficient is negative, but not significant. *Duration* is negative and significant for both monthly and trade returns, indicating trading in shorter time horizons results in better returns, all else being equal. *Spread* is positive and generally insignificant.

The final control variable, *Month_Count*, is positive but not significant with respect to trade returns, although it is negative and significant with respect to monthly returns. The explanation for this is unclear. It could reflect mean reversion given that, as outlined in Section 2.6, our sample appears to be above average in performance. However, we would also expect an effect on the trade returns as well, which we do not find.

We conducted two additional tests which are untabulated for brevity. In the first we replaced *NTrades* and *RPS* with *Turnover* in Equations (3.1) and (3.2). In line with the univariate findings the coefficient values for *Turnover* were strongly negative in the former case, and strongly positive in the latter. Second, we re-ran Equation (3.2) excluding trader fixed effects but included demographic indicators of trader experience, geographic region, and trading style. The results continued to hold.

3.3 The experience factor

Prior research supports the view that behavioral biases such as overconfidence can be overcome through experience (Gervais and Odean, 2001; Nicolosi, et al., 2009; Seru, et al., 2010). Therefore, if, as we argue, *RPS* is a better indicator of investor overconfidence, we would expect to observe a stronger negative association between *RPS* and trade timing for the inexperienced traders relative to experienced traders who are less likely to suffer from such biases.

To examine this, we re-run Equation 3.2, but divide our sample into two experience categories: traders who identified themselves as inexperienced (0-3 years of experience) and those who reported as being experienced (3+ years of experience). We exclude those traders who did not disclose their trading experience. Table 6 reports the estimates for Equation (3.2) based on these two groups. We find for the inexperienced traders (Column (1)), *RPS* is negative and highly significant, while for the experienced traders (Column (2)) *RPS*, although negative, is not significant. Irrespective of experience level, *NTrades*, is positive and significant. Thus, our findings are consistent with the assertion that increases in *RPS* are indicative of behaviorally motivated activity as our experienced traders appear to be able overcome such biases.

With respect to *Month_Count*, in the case of the inexperienced group, the coefficient value is positive and significant. In contrast, the *Month_Count* coefficient for the more experienced traders is negative and significant. This potentially indicates mean reversion with respect to average trade returns. However, the fact that the coefficient value is much more positive for the less experienced group than it is negative for the more experienced group suggests a possible learning aspect.

3.4 Examining possible survivorship with respect to position size

The link between *RPS* and experience level suggests that more experienced traders trade relatively smaller positions because they have developed the ability to reduce the influence of behavioral biases on their decision-making. However, a challenge could be made as to the question of causality. For example, it could be that traders become experienced because they trade smaller than others, and that lower *RPS* reduces the traders' odds of dropping out of the market. In other words, those who trade smaller survive to become more experienced traders.

So, do investors trade smaller because they become experienced and learn that less is better? Or do investors who trade smaller simply last long enough to become experienced? Are we talking about a learned behavior or a survivorship bias? To determine the directionality of this linkage we examine the *RPS* data with respect to trader experience by constructing the following model:

$$RPS_{j,m} = \alpha + \beta_1 NTrades_{j,m} + \beta_2 Balance_{j,m} + \beta_3 Month\_Count_{j,m} + \beta_4 Duration_{j,m} + \beta_5 Spread_{j,m} + \beta_6 Month\ F.E. + \beta_7 Trader\ F.E. + \varepsilon_{j,m} \tag{3.3}$$

All the variables used in Equation (3.3) are as previously defined. *Month_Count* is the variable of interest. If there is no link between experience and *RPS*, then *Month_Count* should not be significant for the less experienced traders.

Table 7 reports the estimates for the Equation (3.3). For the full sample of traders (Column (1)) the coefficient on *Month_Count* is positive but insignificant, indicating that for the broad group of traders time has no meaningful impact on the relative sizes of the positions they take in their trading.

For the inexperienced trader sample (Column (2)), however, *Month_Count* is negative (-0.013) and statistically significant, consistent with the idea that inexperienced traders learn to trade smaller.

Among the control variables in Columns (1) and (2) the coefficient estimates for *Balance*, *Duration*, *Spread*, and *NTrades* are all highly significant in both cases. Those with larger accounts tend to trade smaller, as do those who trade in longer time frames, while those who trade more liquid currency pairs (less negative *Spread*) and who trade more frequently trade relatively larger.

For the purposes of examining whether prior patterns persist, we ran the above analysis for both *Turnover* and *NTrades* using similar models. The unreported results indicate that newer traders don't just learn to reduce *RPS* over time, they also reduce trade frequency. This is consistent with the Mahani and Bernhardt (2007) suggestion that newer traders start trading overly frequently, then learn over time to trim back. Unfortunately, our findings do not offer evidence in support of the idea that newer traders combine high frequency with smaller trades in the learning process – at least not in broad terms. Not surprisingly, given the reduction in *RPS* and trade frequency over time for less experienced traders, we also observe that turnover falls as one remains in the market.

It is worth noting that while the focus of this paper is on retail traders, we likely have at least some professionals in our dataset. They cannot be directly identified, but we can probably safely assume they are among those with the largest account balances. We would expect professionals to exhibit less influence on performance from behavioral effects, and we see evidence for this in Table 4. It shows a -0.58 correlation between *Balance* and *RPS*, which is supported by the negative coefficients for *Balance* in the Table 7 results. We also re-ran Equation 3.2 (Table 5, Column 4) on just the observations where *Balance* is in the top 5% (1681 trader-months, 311 members), assuming this probably captures any professional traders in our sample. In unreported results, we find neither

NTrades nor *RPS* is significant, which fits the narrative that institutional investors don't have the same kind of influences from behavioral biases.

3.5 What kind of overconfidence do these tests capture?

Glaser and Weber (2009) assert that the two primary categories of investor overconfidence – miscalibration (underestimate risk) and misattribution (better-than-average) – have different sources and expressions. Both lead to increased trading activity, but only the latter also motivates increased risk-taking. They provide evidence in favor of prior market returns driving miscalibration-linked overconfidence, while portfolio returns influence misattribution-driven overconfidence. The latter is supported by Ben-David, et al. (2018).

As there are no market returns in foreign exchange, we cannot specifically test for miscalibration-based overconfidence. However, to test for the misattribution variety we can modify Equation (3.3) above by adding lagged returns and extending it to cover trade frequency and currency pair selection.

$$RPS_{j,m} = \alpha + \beta_1 Lagged\_Return_{j,m} + \beta_2 NTrades_{j,m} + \beta_3 Balance_{j,m} + \beta_4 Month\_Count_{j,m} + \beta_5 Duration_{j,m} + \beta_6 Spread_{j,m} + \beta_7 Month\ F.E. + \beta_8 Trader\ F.E. + \varepsilon_{j,m} \tag{3.4}$$

$$NTrades_{j,m} = \alpha + \beta_1 Lagged\_Return_{j,m} + \beta_2\ RPS_{j,m} + \beta_3 Balance_{j,m} + \beta_4 Month\_Count_{j,m} + \beta_5 Duration_{j,m} + \beta_6 Spread_{j,m} + \beta_7 Month\ F.E. + \beta_8 Trader\ F.E. + \varepsilon_{j,m} \tag{3.5}$$

$$Spread_{j,m} = \alpha + \beta_1 Lagged\_Return_{j,m} + \beta_2\ RPS_{j,m} + \beta_3 NTrades_{j,m} + \beta_4 Balance_{j,m} + \beta_5 Month\_Count_{j,m} + \beta_6 Duration_{j,m} + \beta_7 Month\ F.E. + \beta_8 Trader\ F.E. + \varepsilon_{j,m} \tag{3.6}$$

Lagged_Return, our variable of interest, is a winsorized value (top and bottom 1%) of the prior month's net return. All other variables are as previously defined. Given the findings of Glaser and Weber (2009) and Ben-David, et al. (2018), to observe changes in misattribution-based overconfidence we expect to see the measures of trading activity (*NTrades* and *RPS*) increase with increased lagged returns. Similarly, to the extent that *Spread* captures the level of market volatility to which the trader is exposing themselves, we should see that value decline (become more negative indicating trading in currency pairs with larger spreads). As noted by Ben-David, et al. (2018) overconfident traders would be less likely to see prior losses as indicative of their own skill. As such, if there is any negative reaction in trading activity or risk taking after losses, it should be of a lesser magnitude than in the reverse case.

Table 8 presents the results of the regressions based on the three models above. We divide the sample into observations where the prior month's return is positive and those where it is negative. Our results are consistent with the above conjecture. The coefficient on *Lagged_Return* for *RPS* and *NTrades* is positive and significant (0.585 and 0.270 respectively) when prior monthly returns are positive, and negative and significant (-0.465 and -0.189 respectively) when prior return is negative. This is strong evidence in support of changes in *RPS* – the only one of the metrics to be negatively linked with trade timing performance – being reflective of changes in misattribution-based overconfidence.

It is worth noting, however, that while negative prior returns do produce a drop in trading activity that is smaller in magnitude than the increase seen following positive prior returns, it's certainly nowhere near the zero change the literature predicts. We therefore do not see traders taking the attitude that winning months are due to their own skill (increased confidence) and losing months are just bad luck (no change in confidence). As such, it suggests there is some kind of learning effect at work. This fits in with the findings from Section 3.4 where we observed that traders learn to trade relatively smaller over time.

A learning aspect is further made by the coefficient for *Spread* in the positive prior return case actually being less negative than it is positive when prior return is negative (-0.000008 and 0.000014).

The implication of this result is traders are quicker to either narrow their set of traded currency pairs or shift toward higher liquidity/lower volatility pairs after a loss than they are to go in the other direction after a gain. Although, Ben-David, et al. (2018) have "uninformative feedback" as the focal point with respect to prior returns, they too show indications of learning in their results.

There is one additional interesting observation to be made from Table 8. With respect to *RPS*, the coefficient for *Month_Count* is positive and significant in the case of positive prior returns, while it is neither in the negative return case. In line with prior literature it points to traders becoming increasingly overconfident over time when they have winning months, while experience has no impact on *RPS* following losing ones. Consider, however, the general pattern of trader performance as outlined in Section 2.6 in which the traders are only profitable in about 40% of their months on average. That means they are taking losses more often than making profits – even more so for inexperienced traders, as we would expect – which explains the findings reported in Section 3.4 above of newer traders reducing *RPS* over time.

3.6 Additional Analysis

We observed in Table 2 that for those traders who did not provide any indication of their experience levels there was a notably different pattern of trading with respect to their currency pair selections. To assess the sensitivity of our results to alternative samples, we explored whether this sub-sample group of traders influences the findings at all. In unreported analysis, we find our results are not sensitive to their exclusion.

As noted in Section 2.1, the data set comprises traders who became part of a social network. The collection process included a mechanism for gathering pre-membership data from member accounts (where available) identical to the collection of on-going data. To examine the potential influence of network membership on our findings we re-ran all our prior analysis including a membership dummy variable for each monthly observation period to indicate whether the trader was in the network at the point of the trades or not. Our results are not sensitive to this specification and provide some evidence that network membership does not significantly change trader behavior.

We further examined whether our results are influenced by the degree to which traders drop out of our sample. Specifically, there may be a group of traders in our sample who perhaps are drawn into the retail forex market by aggressive marketing techniques with a "get rich quick" type of approach who quickly suffer excessive losses, or realize they lack the skill to trade the market profitably and drop out. Unfortunately, the data does not provide a clear date for when traders ceased trading and exit the network. We can only infer it from the date of a trader's last recorded transaction.

We therefore attempt to identify traders who remain "active" and those who appear to be "quitters". Specifically, we focus on those traders who joined the network prior to the final 12 months of our study period and identify traders who were still actively trading in the final six months of the sample (673 member, 11,989 trader-months) as "active" traders, and those traders who were not active in the last six months as "quitter" traders (3,734 members, 18,497 trader-months). We acknowledge that it is possible that traders we identify as "quitter" did not leave the forex market all together, but merely stopped trading in the account(s) linked to the network.

In the case of 'active' traders, they have a mean (median) of 17.82 (16) months of trading activity and 26.56 (27) calendar months in the dataset, while for the 'quitters' it is 4.95 (3) and 7.02 (4) respectively. In terms of experience, traders with 0-3 years of experience dominate the 'quitter' group compared to those with 3+ years of experience (2,393 vs. 873). However, this is only slightly more imbalanced than the full sample ratio (73% vs. 68%). For the 'active' group, again the less experienced traders dominate at 59% of the total (323 vs 232). Overall, both groups are reasonably representative of the full sample.

Table 9 reports the estimates for Equation (3.2) in Columns (1) and (2) and for Equation (3.3) in Columns (3) and (4). We find the results for both sub-samples - 'active' traders and 'quitter' traders reported in Column (1) and (2) respectively - are consistent with our main analysis. *RPS* is negative and significant and *NTrades* is positive and significant. Neither group influences our conclusions. With respect to *RPS*, the *Month_Count* coefficients for both the 'active' and 'quitter' groups are negative and significant, consistent with the analysis for the inexperienced group. One might expect to see the 'quitter' group showing less learning with respect to changing *RPS* compared to those that stayed active, however that does not appear to be the case. Quite the opposite, actually. This may reflect that the 'quitter' group have a higher general *RPS* level. Their mean (median) *RPS* of 15.61 (6.53) compares to 9.96 (3.63) for the 'active' group. They may simply not have been in the dataset long enough for their RPS levels to drop to be more in line.

4 Conclusion

The extant literature with respect to overconfidence and its influence on investors has focused on the activity metrics of account turnover and trade frequency in drawing a link between the behavioral bias and excessive trading. We, however, hypothesize that relative position size, a contributor of turnover, is a more direct indicator of overconfidence given trade frequency is subject to conflicting influences. Our findings support this hypothesis. While it may be that increased overconfidence does drive more frequent trading, we actually find that higher trade frequency is associated with improved trade timing performance, as is higher turnover. The opposite is true for increased relative position size, making the latter the more meaningful metric to observe.

With respect to looking for investor confidence, we acknowledge that lacking a direct indication at the time of trade decision-making (or perhaps prior to that in the strategy conception phase) we cannot be sure what we see in their actions is in fact overconfidence driven. All we can do is observe likely effects. In this paper we follow the "overconfidence leads to excessive market participation" suggestion of the literature (beginning with Odean (1999)) and find increased relative positions size is part of that over-trading. Moreover, our analysis indicates mean positions size is heavily influenced by factors we control for in our trade timing performance model. The fraction unaccounted for is likely to include at least some behavioral element. The finding that relative position size is negatively linked to trade timing performance and also linked with prior trading returns is evidence in favor of those hypotheses. We do not contend that poor trade timing is *only* the result of overconfidence. There are many factors which could contribute. Rather, we point to the fact that reduced trade timing performance goes together with over-trading, consistent with a likely behaviorally bias.

Our findings contribute to the literature in three primary ways. First, we extend the research into overconfidence among financial markets participants with respect to the impact of overconfident trading in that it doesn't just lead to excessive activity, but also to impaired trade timing. This presents an interesting new direction for future research. Can we identify the actual factors at work driving that impaired performance? For example, do traders become more prone to disposition effect influences on their trading? That has potential implications on risk management applications and prospective regulatory considerations.

Second, we expand the research into the link between experience and investor sophistication on overconfidence and other behavioral biases, especially with respect to how experience relates to learning to overcome such biases. Related to that, we also extend the literature with respect to the paths investors take in the learning process, with a connection to the type of overconfidence suffered – in this case primarily misattribution. This has implications for investor education efforts, and even potentially training at the professional level.

Finally, we further the research in to the performance and behavior of individual speculators, especially those operating in a high frequency environment, and specifically those operating in the retail forex market where the research is still in its infancy. Position size, in particular, has until now received only a limited amount of attention. Additionally, aside from the confidence aspects, our findings address some of the questions related to the differences between those who drop out of the market and those who carry on longer-term.

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Table 1: Trader Descriptive Statistics

Panel A: Trader Monthly Activity and Performance

Sample of 5,349 retail aggregator based foreign exchange traders for the period July 2009 to April 2013 comprising 33,633 trader-months of observations. All variables are based on aggregated values for traders with multiple accounts (where applicable). *Balance* is the average daily aggregated account balance for a trader in month *m*. *Duration* is the average position-holding period (open to close) for round-turn trades initiated in a month *m*, measured in days. *Spread* is the mean bid/ask spread of trades initiated in a given month *m* expressed as a return based on the exchange rate at which each trade was entered (always negative). *Turnover* is calculated as total volume traded in month *m* divided by the average daily balance. *NTrades* is the number of completed round-turn positions initiated in month *m*. *Relative Position Size* is the average size of the trades initiated in month *m* relative to the account balance, expressed as a multiple of the account balance. *Monthly Return* is derived using a weighting based on capital balances for included accounts. Returns are based on the compounded daily returns calculated by the social network platform. *Average Trade Return* is the mean of the returns of trades done in month *m* assuming no leverage use, thus accounting only for the exchange rate movement.

	Mean	**Std. Dev.**	**25^{th} Q**	**Median**	**75^{th} Q**
Balance (USD Equivalent)	$14,643	$87,760	$342	$1,511	$5,858
NTrades	74	220	6	22	66
Duration (Days)	3.63	20.54	0.11	0.45	1.68
Turnover (X:1)	498	3259	26	107	376
RPS (X:1)	12.96	22.57	1.51	4.90	14.14
Traded Months in Sample	6.29	7.21	1	3	8
Calendar Months in Sample	8.91	10.21	1	4	13
Monthly Return	-0.0594	0.3109	-0.1549	-0.0183	0.0357
Average Trade Return	-0.000501	0.008402	-0.000827	-0.000094	0.000550
Spread	-0.000146	0.000076	-0.000174	-0.000136	-0.000094

Panel B: Comparison of Member Quarterly Profitability Percentages to a Broader FX Market

Distribution of quarterly member account profitability rates compared to those reported by US brokers as mandated by the CFTC. Profitability rates are based on accounts with at least one transaction in the given quarter. Source: Forex Magnates

	US Broker Reported by CFTC			Sample			
Quarter	# of Accounts	Profitable	%	# of Accounts	Profitable	%	Diff.
Q4 2009	92,024	25,943	28.2%	226	75	33.2%	5.0%
Q1 2010	81,289	21,854	26.9%	1,592	565	35.5%	8.6%
Q2 2010	106,650	28,176	26.4%	2,592	868	33.5%	7.1%
Q3 2010	100,320	29,026	28.9%	2,835	889	31.4%	2.4%
Q4 2010	108,361	31,242	28.8%	2,636	915	34.7%	5.9%
Q1 2011	108,513	34,620	31.9%	2,561	867	33.9%	1.9%
Q2 2011	106,945	28,765	26.9%	2,320	877	37.8%	10.9%
Q3 2011	108,490	32,512	30.0%	2,302	950	41.3%	11.3%
Q4 2011	97,206	33,953	34.9%	2,106	970	46.1%	11.1%
Q1 2012	97,281	32,370	33.3%	2,170	896	41.3%	8.0%
Q2 2012	93,687	29,884	31.9%	2,062	901	43.7%	11.8%
Q3 2012	101,020	32,731	32.4%	1,872	788	42.1%	9.7%
Q4 2012	89,567	32,131	35.9%	1,752	786	44.9%	9.0%
Q1 2013	99,207	34,918	35.2%	1,785	799	44.8%	9.6%
		Average:	30.8%		Average:	38.9%	8.0%

Panel C: Experience, Residence and Trading styles

The experience, geographic region, and trading style classifications are obtained from trader profile indications.

	Members	Trader-Months		Members	Trader-Months
Total	**5,349**	**33,633**	***Trading Style*:**		
Experience Level:			Technical Analysis	2,847	20,060
0-1 years of experience	1,157	6,422	Fundamental Anal.	207	1,478
1-3 years of experience	1,731	12,076	Momentum	229	1,657
3-5 years of experience	481	3,606	News	75	534
5+ years of experience	907	7,184	None of the above	510	3,226
No disclosure of experience	1,073	4,345	No disclosure of style	1,481	6,678
Geographical residence:					
United States	1,413	11,208			
Europe	1,749	11,058			
Asia/Pacific	902	5,601			
No Entry	1,285	5,766			

Table 2: Currency Selection and Trading Volumes of Retail Foreign Exchange Traders

Panel A: Proportion of traded volume by currency

Sample of 5,349 retail aggregator based foreign exchange traders for the period July 2009 to April 2013. The BIS rows provide comparative data for spot trading from BIS (2014).

	USD	EUR	GBP	JPY	AUD	CHF	CAD
Full Sample (n = 2,662,844)	88.8%	72.1%	17.0%	7.3%	5.1%	4.7%	2.5%
No disclosure of experience	97.1%	91.7%	3.6%	3.6%	1.6%	1.1%	0.6%
0-1 years of experience (n = 332,802)	82.5%	50.3%	31.6%	12.4%	9.5%	7.0%	3.3%
1-3 years of experience (n = 806,312)	81.1%	53.5%	28.0%	13.5%	8.2%	6.5%	5.6%
3-5 years of experience (n = 327,633)	75.2%	55.2%	27.1%	11.2%	12.3%	7.0%	2.8%
5+ years of experience (n = 833,663)	83.3%	56.2%	28.9%	8.9%	6.9%	8.7%	4.0%
BIS	82.6%	36.9%	11.1%	29.9%	9.6%	4.1%	4.5%

Panel B: Proportion of traded volume by currency pair

There is no separate reporting for GBP/JPY in BIS (2014), so it is omitted here in Panel B.

	EUR/USD	GBP/USD	AUD/USD	USD/JPY	EUR/JPY	USD/CHF	USD/CAD	GBP/JPY	EUR/GBP	EUR/CHF
Full Sample	65.8%	13.3%	2.9%	2.3%	2.5%	1.6%	1.5%	1.5%	1.0%	2.1%
No disclosure of experience	90.2%	2.8%	0.9%	2.0%	0.6%	0.4%	0.4%	0.5%	0.2%	0.5%
0-1 years of experience	39.9%	24.1%	7.0%	3.9%	3.7%	3.2%	2.2%	3.2%	2.7%	2.4%
1-3 years of experience	43.5%	20.1%	5.3%	3.3%	4.7%	3.0%	3.4%	4.0%	1.4%	1.9%
3-5 years of experience	45.5%	20.0%	3.3%	1.6%	5.0%	1.2%	2.2%	3.7%	0.6%	3.2%
5+ years of experience	45.2%	23.8%	4.6%	2.2%	3.7%	3.0%	2.4%	1.3%	1.8%	4.5%
BIS	24.3%	10.4%	10.3%	21.3%	4.9%	3.0%	5.6%		2.6%	1.6%

Table 3: Trader Quintiles Analysis

Sample of 5,349 retail aggregator based foreign exchange traders for the period July 2009 to April 2013 comprising 33,633 trader-months of observations (one trader-month being the performance of one individual in a single month). All variables are as previously defined. Q5-Q1 Returns indicates the return differentials between the most active (Q5) and least active (Q1) quintiles. *** represent significance levels at 99% or better based on a two-sample T-test (two-tailed). All variables are as previously defined in Table 1.

Panel A: Trader Monthly Return Quintiles Based on Turnover

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Turnover	8	42	117	313	2016
Balance	$18,331	$18,764	$20,543	$10,241	$5,300
RPS	2.73	8.08	11.80	15.30	26.99
NTrades	10	30	60	86	183
Monthly Return	-0.0104	-0.0132	-0.0334	-0.0627	-0.1776
Q5 - Q1 Returns	-0.1671***				

Panel B: Trader Monthly Return Quintiles Based on Trade Frequency

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
NTrades	2	9	24	56	281
Balance	$6,866	$9,500	$11,075	$13,866	$32,363
Turnover	42	142	304	573	1454
RPS	18.74	15.47	12.97	10.50	6.72
Monthly Return	-0.0400	-0.0417	-0.0561	-0.0713	-0.0889
Q5 - Q1 Returns	-0.0489***				

Panel C: Trader Monthly Return Quintiles Based on Relative Position Size

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
RPS	0.63	2.21	5.32	12.10	44.69
Balance	$42,650	$17,746	$7,039	$4,258	$1,387
Turnover	69	189	301	545	1389
NTrades	141	89	58	47	33
Monthly Return	-0.0042	-0.0201	-0.0351	-0.0676	-0.1704
Q5 - Q1 Returns	-0.1662***				

Panel D: Average Trade Return Quintiles Based on Turnover, Trade Frequency, and Relative Position Size

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Turnover	-0.00116	-0.00050	-0.00038	-0.00024	-0.00024
Q5 - Q1 Returns	0.00092***				
NTrades	-0.00138	-0.00059	-0.00017	-0.00015	-0.00013
Q5 - Q1 Returns	0.00125***				
RPS	-0.00049	-0.00050	-0.00036	-0.00046	-0.00069
Q5 - Q1 Returns	-0.00019				

Panel E: Monthly Return 2-Way Sort Quintiles Based on Trade Frequency and Relative Position Size

	NTrades Q1 (NTr Q1)						RPS Q1				
	RPS Q1	RPS Q2	RPS Q3	RPS Q4	RPS Q5		NTr Q1	NTr Q2	NTr Q3	NTr Q4	NTr Q5
Obs	1285	1173	1204	1473	2095	Obs	1285	1009	1037	1240	2178
RPS	1	2	5	12	51	NTrades	2	9	24	57	386
Return	-0.56%	-0.97%	-2.09%	-2.93%	-9.65%	Return	-0.56%	-0.90%	-0.47%	0.55%	-0.65%
	NTrades Q2 (NTr Q2)						**RPS Q2**				
	RPS Q1	**RPS Q2**	**RPS Q3**	**RPS Q4**	**RPS Q5**		**NTr Q1**	**NTr Q2**	**NTr Q3**	**NTr Q4**	**NTr Q5**
Obs	1009	1109	1314	1478	1584	Obs	1173	1109	1242	1510	1693
RPS	1	2	5	12	46	NTrades	2	10	24	57	279
Return	-0.89%	-0.58%	-0.89%	-2.73%	-12.82%	Return	-0.97%	-0.58%	-1.04%	-1.70%	-4.65%
	NTrades Q3 (NTr Q3)						**RPS Q3**				
	RPS Q1	**RPS Q2**	**RPS Q3**	**RPS Q4**	**RPS Q5**		**NTr Q1**	**NTr Q2**	**NTr Q3**	**NTr Q4**	**NTr Q5**
Obs	1037	1242	1479	1450	1354	Obs	1204	1314	1479	1516	1211
RPS	1	2	5	1203	41	NTrades	3	9	24	56	210
Return	-0.47%	-1.04%	-2.35%	-4.22%	-18.79%	Return	-2.09%	-0.89%	-2.35%	-4.03%	-8.50%
	NTrades Q4 (NTr Q4)						**RPS Q4**				
	RPS Q1	**RPS Q2**	**RPS Q3**	**RPS Q4**	**RPS Q5**		**NTr Q1**	**NTr Q2**	**NTr Q3**	**NTr Q4**	**NTr Q5**
Obs	1240	1510	1516	1322	1087	Obs	1473	1478	1450	1322	1003
RPS	1	2	5	12	39	NTrades	2	9	23	56	192
Return	0.55%	-1.70%	-4.03%	-9.87%	-24.43%	Return	-2.93%	-2.73%	-4.22%	-9.87%	-17.91%
	NTrades Q5 (NTr Q5)						**RPS Q5**				
	RPS Q1	**RPS Q2**	**RPS Q3**	**RPS Q4**	**RPS Q5**		**NTr Q1**	**NTr Q2**	**NTr Q3**	**NTr Q4**	**NTr Q5**
Obs	2178	1693	1211	1003	587	Obs	2095	1584	1354	1087	587
RPS	1	2	5	12	37	NTrades	2	9	23	54	195
Return	-0.65%	-4.65%	-8.51%	-17.91%	-37.11%	Return	-9.65%	-12.82%	-18.79%	-24.43%	-37.11%

Panel F: Average Trade Return 2-Way Sort Quintiles on Trade Frequency and Relative Position Size

	NTrades Q1 (NTr Q1)						RPS Q1				
	RPS Q1	RPS Q2	RPS Q3	RPS Q4	RPS Q5		NTr Q1	NTr Q2	NTr Q3	NTr Q4	NTr Q5
Obs	1285	1173	1204	1473	2095	Obs	1285	1009	1037	1240	2178
RPS	1	2	5	12	51	NTrades	2	9	24	57	386
Avg. Rtn	-0.124%	-0.206%	-0.118%	-0.110%	-0.141%	Avg. Rtn	-0.124%	-0.133%	0.003%	-0.017%	-0.010%
	NTrades Q2 (NTr Q2)						**RPS Q2**				
	RPS Q1	**RPS Q2**	**RPS Q3**	**RPS Q4**	**RPS Q5**		**NTr Q1**	**NTr Q2**	**NTr Q3**	**NTr Q4**	**NTr Q5**
Obs	1009	1109	1314	1478	1584	Obs	1173	1109	1242	1510	1693
RPS	1	2	5	12	46	NTrades	2	10	24	57	279
Avg. Rtn	-0.133%	-0.044%	-0.032%	-0.052%	-0.051%	Avg. Rtn	-0.206%	-0.044%	-0.015%	-0.002%	-0.016%
	NTrades Q3 (NTr Q3)						**RPS Q3**				
	RPS Q1	**RPS Q2**	**RPS Q3**	**RPS Q4**	**RPS Q5**		**NTr Q1**	**NTr Q2**	**NTr Q3**	**NTr Q4**	**NTr Q5**
Obs	1037	1242	1479	1450	1354	Obs	1204	1314	1479	1516	1211
RPS	1	2	5	1203	41	NTrades	3	9	24	56	210
Avg. Rtn	0.003%	-0.015%	-0.017%	-0.017%	-0.036%	Avg. Rtn	-0.118%	-0.032%	-0.017%	-0.012%	-0.013%
	NTrades Q4 (NTr Q4)						**RPS Q4**				
	RPS Q1	**RPS Q2**	**RPS Q3**	**RPS Q4**	**RPS Q5**		**NTr Q1**	**NTr Q2**	**NTr Q3**	**NTr Q4**	**NTr Q5**
Obs	1240	1510	1516	1322	1087	Obs	1473	1478	1450	1322	1003
RPS	1	2	5	12	39	NTrades	2	9	23	56	192
Avg. Rtn	-0.017%	-0.002%	-0.012%	-0.023%	-0.024%	Avg. Rtn	-0.110%	-0.052%	-0.017%	-0.023%	-0.016%
	NTrades Q5 (NTr Q5)						**RPS Q5**				
	RPS Q1	**RPS Q2**	**RPS Q3**	**RPS Q4**	**RPS Q5**		**NTr Q1**	**NTr Q2**	**NTr Q3**	**NTr Q4**	**NTr Q5**
Obs	2178	1693	1211	1003	587	Obs	2095	1584	1354	1087	587
RPS	1	2	5	12	37	NTrades	2	9	23	54	195
Avg.Rtn	-0.010%	-0.016%	-0.013%	-0.016%	-0.018%	Avg. Rtn	-0.141%	-0.051%	-0.036%	-0.024%	-0.018%

Table 4: Correlation Matrix of Return Metrics and Control Variables

Sample of 5,349 retail aggregator based foreign exchange traders for the period July 2009 to April 2013 comprising 33,633 trader-months of observations (one trader-month being the performance of one individual in a single month). *Month_Count* is the number of calendar months since the individual joined the network (negative for pre-membership). *Lagged_Return* is the trader's monthly return from their prior month of activity. All other variables are as previously defined. A log transformation to *Balance, Duration*, *Turnover*, *RPS*, and *NTrades* has been applied. All variables, aside from *Spread* and *Month_Count*, have been winsorized at the top and bottom 1%. P-values presented in parentheses.

	Monthly Return	***Avg. Trade Return***	***Turnover***	***NTrades***	***RPS***	***Balance***	***Duration***	***Spread***	***Month Count***
Monthly Return	1.00								
Average_Trade_Return	0.27	1.00							
	(0.00)								
Turnover	-0.23	0.03	1.00						
	(0.00)	*(0.00)*							
NTrades	-0.07	0.08	0.65	1.00					
	(0.00)	*(0.00)*	*(0.00)*						
RPS	-0.23	-0.05	0.60	-0.22	1.00				
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*					
Balance	0.17	0.04	-0.25	0.25	-0.58	1.00			
	(0.00)	*(0.55)*	*(0.00)*	*(0.00)*	*(0.00)*				
Duration	0.04	-0.08	-0.28	-0.04	-0.32	0.15	1.00		
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*			
Spread	-0.00	0.02	0.12	0.02	0.14	-0.03	-0.24	1.00	
	(0.83)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*		
Month_Count	-0.01	0.00	-0.08	-0.05	-0.04	-0.08	0.09	-0.05	1.00
	(0.04)	*(0.49)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	
Lagged_Return	0.14	0.04	-0.14	0.02	-0.20	0.20	0.09	0.00	-0.02
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.80)*	*(0.00)*

Table 5: Influence of Trade Frequency and Relative Position Size on Monthly Returns and Monthly Average Trade Returns

$$Monthly\_Return_{j,m} = \alpha + \beta_1 NTrades_{j,m} + \beta_2 RPS_{j,m} + \beta_3 Balance_{j,m} + \beta_4 Month\_Count_{j,m} + \beta_5 Duration_{j,m} + \beta_6 Spread_{j,m} + + \beta_7 Month\ F.E. + \beta_8 Trader\ F.E + \varepsilon_{j,m} \quad (3.1)$$

$$Average\_Trade\_Return_{j,m} = \alpha + \beta_1 NTrades_{j,m} + \beta_2 RPS_{j,m} + \beta_3 Balance_{j,m} + \beta_4 Month\_Count_{j,m} + \beta_5 Duration_{j,m} + \beta_6 Spread_{j,m} + + \beta_7 Month\ F.E. + \beta_8 Trader\ F.E + \varepsilon_{j,m} \quad (3.2)$$

The table reports the ordinary least squares estimation results for the period July 2009 to April 2013. The dependent variables, *Monthly_Return* and *Average_Trade_Return*, are multiplied by 10,000 so all coefficients can be interpreted in terms of basis points. Coefficient values are thus expressed such that, for example, the coefficient of -254.8 on *NTrades* in the first column indicates a 1-point decrease in the log of the number of monthly trades (*NTrades*) equates to a 254.8 basis point decrease in monthly returns. Heterokedasticity-robust standard errors are clustered by trader. All random variables exclusive of *Spread* and *Month_Count* are winsorized at 1% top and bottom. t-statistics are reported in parentheses. *, ** and *** represent significance levels of 90%, 95% and 99% respectively. All variable definitions are as reported in Table 1. Our variables of interest are *NTrades* and *RPS*.

Dependent Variable	Monthly Returns			Average Trade Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
NTrades	**-254.8*** **		**-244.4*** **	**2.454*** **		**2.487*** **
	(-15.00)		**(-14.88)**	**(7.73)**		**(7.81)**
RPS		**-440.1*** **	**-426.7*** **		**-1.205*** **	**-1.341*** **
		(-16.46)	**(-16.45)**		**(-2.95)**	**(-3.30)**
Balance	339.9***	12.7	104.7***	-0.033	0.163	-0.773*
	(12.01)	(0.42)	(3.43)	(-0.09)	(0.41)	(-1.87)
Month Count	-34.9***	33.5***	-34.9***	0.051	0.036	0.051
	(-14.43)	(-14.31)	(-14.97)	(1.23)	(0.89)	(1.24)
Duration	-103.3***	-123.0***	-137.5***	-2.952***	-3.206***	-3.059***
	(-8.23)	(-9.72)	(-10.91)	(-8.86)	(-9.34)	(-9.20)
Spread	111,095.7	591,731.5*	551,412.3*	6058.000	7031.824	7442.184
	(0.36)	(1.92)	(1.82)	(0.60)	(0.69)	(0.73)
Intercept	-1,954.7***	250.9	419.8	-12.449	-3.265	-4.984
	(-3.94)	(0.44)	(0.79)	(-1.00)	(-0.26)	(-0.39)
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Trader Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Traders	5,348	5,348	5,348	5,348	5,348	5,348
N	33,629	33,629	33,629	33,629	33,629	33,629
Adjusted R2	15.86%	16.22%	17.21%	8.48%	8.08%	8.53%

Table 6: Trading Activity Influence on Monthly Average Trade Returns Based on Trader Experience Level

$$Average\_Trade\_Return_{j,m} = \alpha + \beta_1 NTrades_{j,m} + \beta_2 RPS_{j,m} + \beta_3 Balance_{j,m} + \beta_4 Duration_{j,m} + \beta_5 Spread_{j,m} + \beta_6 Month\_Count_{j,m} + \beta_7 Month\ F.E. + \beta_8 Trader\ F.E + \varepsilon_{j,m} \quad (3.2)$$

The table reports the ordinary least squares estimation results for the period July 2009 to April 2013. The *Experience* category splits are based on indications from each individual (those with no entry are excluded). The dependent variable, *Average_Trade_Return*, is multiplied by 10,000 so all coefficients can be interpreted in terms of basis points. Coefficient values are thus expressed such that, for example, a 1-point increase in the log of the number of monthly trades (*NTrades*) results in a 3.07 basis point increase in mean trade return see Column (1) below. Heterokedasticity-robust standard errors are clustered by trader. All random variables exclusive of *Spread* and *Month_Count* are winsorized at 1% top and bottom. t-statitstics are reported in parentheses. *, ** and *** represent significance levels of 90%, 95% and 99% respectively.. All variable definitions are as reported in Table 1. Our variables of interest are *NTrades* and *RPS*.

Dependent Variable	*Average_Trade_Return*	
	0-3 years experience	**3+ years experience**
	(1)	(2)
NTrades	**3.069*** **	**1. 427** **
	(7.21)	**(2.35)**
RPS	**-1.363** **	**-1.193**
	(-2.36)	**(-1.59)**
Balance	-0.764	-0.735
	(-1.26)	(-1.09)
Month_Count	0.264***	-0.174**
	(2.84)	(-2.27)
Duration	-3.693***	-2.388***
	(-7.85)	(-4.14)
Spread	2057.311	4320.772
	(0.16)	(0.22)
Intercept	4.173	-18.003
	(0.48)	(-0.74)
Month Fixed Effects	Yes	Yes
Trader Fixed Effects	Yes	Yes
Traders	2,877	1,388
N	18,495	10,789
Adjusted R^2	7.83%	8.44%

Table 7: Experience Influence on Monthly Mean Relative Position Size

$$RPS_{j,m} = \alpha + \beta_1 MonthCount_{j,m} + \beta_2 NTrades_{j,m} + \beta_3 Balance_{j,m} + \beta_4 Duration_{j,m} + \beta_5 Spread_{j,m} + \beta_6 Month\ F.E. + \beta_8 Trader\ F.E + \varepsilon_{j,m} \tag{3.3}$$

The table reports the ordinary least squares estimation results for the period July 2009 to April 2013. Coefficient values are expressed in terms of the log of RPS such that, for example, a 1-point increase in the *Month_Count* for inexperienced traders results in a 0.013 decline in the log of average trade leverage, as indicated in Colum (2). The *Experience* category split is based on indications from each individual (those with no entry are excluded). Heterokedasticity-robust standard errors are clustered by trader. All random variables exclusive of *Spread* and *Month_Count* are winsorized at 1% top and bottom. t-statistics are reported in parentheses. *, ** and *** represent significance levels of 90%, 95% and 99% respectively. All variable definitions are as reported in Table 1. Our variable of interest is *Month_Count*.

Test	**Full Sample** (1)	**0-3 years experience** (2)
Month_Count	**0.000**	**-0.013*** **
	(0.03)	**(-6.37)**
Trades	0.024***	0.035***
	(3.06)	(3.59)
Balance	-0.551***	-0.575***
	(-38.86)	(-31.79)
Duration	-0.080***	-0.077***
	(-12.73)	(-9.85)
Spread	1031.868***	1186.213***
	(5.58)	(6.60)
Intercept	5.565***	6.553***
	(16.92)	(11.29)
Monthly Fixed Effects	Yes	Yes
Trader Fixed Effects	Yes	Yes
Traders	5,348	2,877
N	33,629	18,495
Adjusted R^2	78.43%	79.17%

Table 8: Influence of Prior Returns on Monthly Mean Relative Position Size, Trade Frequency, and Currency Pair Selection

$$RPS_{j,m} = a + \beta_1 Lagged\_Return_{j,m} + \beta_2 NTrades_{j,m} + \beta_3 Balance_{j,m} + \beta_4 Month\_Count_{j,m} + \beta_5 Duration_{j,m} + \beta_6 Spread_{j,m} + \beta_7 Month\ F.E. + \beta_8 Trader\ F.E. + \varepsilon_{j,m} \tag{3.4}$$

$$NTrades_{j,m} = a + \beta_1 Lagged\_Return_{j,m} + \beta_2 RPS_{j,m} + \beta_3 Balance_{j,m} + \beta_4 Month\_Count_{j,m} + \beta_5 Duration_{j,m} + \beta_6 Spread_{j,m} + \beta_7 Month\ F.E. + \beta_8 Trader\ F.E. + \varepsilon_{j,m} \tag{3.5}$$

$$Spread_{j,m} = a + \beta_1 Lagged\_Return_{j,m} + \beta_2 RPS_{j,m} + \beta_3 NTrades_{j,m} + \beta_4 Balance_{j,m} + \beta_5 Month\_Count_{j,m} + \beta_6 Duration_{j,m} + \beta_7 Month\ F.E. + \beta_8 Trader\ F.E. + \varepsilon_{j,m} \tag{3.6}$$

The table reports the ordinary least squares estimation results for the period July 2009 to April 2013. Coefficient values are expressed in terms of logs of the dependent variables such that, for example, a 1-point increase in the *Lagged_Return* when a trader was profitable in their prior month of activity results in a 0.585 increase in the log of average trader *RPS* per Column (1). Heterokedasticity-robust standard errors are clustered by trader. All random variables exclusive of *Spread* and *Month_Count* are winsorized at 1% top and bottom. t-statistics are reported in parentheses. *, ** and *** represent significance levels of 90%, 95% and 99% respectively. All variable definitions are as reported in Table 1. Our variable of interest is *Lagged_Return*.

	Prior Month Profitable			**Prior Month Unprofitable**		
	RPS	**NTrades**	**Spread**	**RPS**	**NTrades**	**Spread**
Test	(1)	(2)	(3)	(4)	(5)	(6)
Lagged_Return	**0.585*** **	**0.270*** **	**-0.079** **	**-0.465*** **	**-0.189*** **	**0.135*** **
	(8.59)	**(3.21)**	**(-1.96)**	**(-9.01)**	**(-2.77)**	**(3.45)**
Balance	-0.481***	0.303***	0.021	-0.563***	0.395***	0.050***
	(-19.96)	(10.51)	(1.50)	(-32.82)	(17.65)	(3.69)
Duration	-0.105***	-0.078***	-0.039***	-0.077***	-0.085***	-0.048***
	(-9.43)	(-4.34)	(-3.07)	(-9.14)	(-6.63)	(-7.89)
Month_Count	0.014***	-0.025***	0.002*	0.002	-0.045***	-0.016***
	(5.72)	(-9.43)	(1.82)	(1.34)	(-22.63)	(-11.52)
RPS		-0.076***	0.059***		0.079***	0.069***
		(-2.64)	(3.44)		(3.35)	(4.91)
NTrades	-0.037***		-0.006	0.035***		-0.010
	(-2.62)		(-0.62)	(3.33)		(-1.43)
Spread	1101.435***	-232.357		1103.365***	-359.436	
	(3.26)	(-0.61)		(5.12)	(-1.38)	
Intercept	5.669***	1.342	-1.969***	5.301***	0.906*	-2.311***
	(7.69)	(1.64)	(-11.07)	(15.28)	(1.83)	(-10.56)
Monthly Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Trader Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Traders	2,959	2,959	2,959	3,553	3,553	3,553
N	11,421	11,421	11,421	16,862	16,862	16,862
Adjusted R²	79.73%	79.15%	64.31%	56.37%	54.62%	44.73%

Table 9: Sensitivity of results to 'active' traders vs. 'quitter' traders

$$Average\_Trade\_Return_{j,m} = \alpha + \beta_1 NTrades_{j,m} + \beta_2 RPS_{j,m} + \beta_3 Balance_{j,m} + \beta_4 Duration_{j,m} + \beta_5 Spread_{j,m} + \beta_6 Month\_Count_{j,m} + \beta_7 Month\ F.E. + \beta_8 Trader\ F.E + \varepsilon_{j,m} \quad (3.2)$$

$$RPS_{j,m} = \alpha + \beta_1 Month\_Count_{j,m} + \beta_2 NTrades_{j,m} + \beta_3 Balance_{j,m} + \beta_4 Duration_{j,m} + \beta_5 Spread_{j,m} + \beta_6 Month\ F.E. + \beta_8 Trader\ F.E + \varepsilon_{j,m} \quad (3.3)$$

The table reports the ordinary least squares estimation results for the period July 2009 to April 2013. The sample includes traders who did their first trade at least 12 months prior to the end of the sample period. It is then divided between those who still had activity in the final six months ("Active") and those who did not ("Quitter"). The dependent variable for Columns (1) and (2), *Average_Trade_Return*, has been multiplied by 10,000 so that coefficients are expressed in terms of basis points. For example, a 1-point increase in *NTrades* results in a 1.62bp increase in the trade return for traders who remained active through the end of the sample period per Column (1). In the RPS results (Columns (3) and (4)), the coefficients are expressed in terms of the log of *RPS*. Heterokedasticity-robust standard errors are clustered by trader. All random variables exclusive of *Spread* and *Month_Count* are winsorized at 1% top and bottom. t-statistics are reported in parentheses. *, ** and *** represent significance levels of 90%, 95% and 99% respectively. All variable definitions are as reported in Table 1. Our variables of interest for Columns (1) and (2) are *NTrades* and *RPS*, and *Month_Count* for Columns (3) and (4).

Dependent Variable	***Average_Trade_Return***		***RPS***	
	Active	**Quitter**	**Active**	**Quitter**
	(1)	(2)	(3)	(4)
NTrades	**1.615*** **	**3.239*** **	0.026**	0.024**
	(3.15)	**(7.22)**	(1.96)	(2.30)
RPS	**-1.534** **	**-1.168** **		
	(-2.56)	**(-1.99)**		
Month_Count	-0. 027	-0.098*	**-0.005*** **	**-0.015*** **
	(-0.55)	(-1.95)	**(-4.38)**	**(10.60)**
Balance	-0.988	-0.617	-0.567***	-0.538***
	(-1.63)	(-1.03)	(-26.16)	(-28.60)
Duration	-2.117***	-3.969***	-0.103***	-0.068***
	(-3.85)	(-9.08)	(-10.00)	(-8.29)
Spread	7165.129	5948.682	813.101***	1343.764***
	(0. 46)	(0.46)	(3.80)	(4.17)
Intercept	-21.676	0.104	5.411***	6.046***
	(-0.97)	(0.01)	(13.17)	(12.72)
Month Fixed Effects	Yes	Yes	Yes	Yes
Trader Fixed Effects	Yes	Yes	Yes	Yes
Traders	673	3,734	673	3,734
N	11,989	18,497	11,989	18,497
Adjusted R^2	5.04%	10.71%	77.03%	78.00%